

Personal Authentication by Using Multi-channel Electroencephalography

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Abstract – We propose a method of electroencephalograph (EEG) authentication by using multi-channel EEG recording, appropriate artifact removal, feature extraction, and machine learning towards improving the authentication accuracy. The results of one subject showed relatively high ACC, low FAR and low FRR in both conditions. The results show good performance as authentication. However, results of other subjects in both conditions showed that either FAR or FRR or both are high.

I. INTRODUCTION

Biometric authentication technologies such as fingerprint, iris, face, and voice print have been developed. Biometric information has high authentication performance, but its authentication system can be falsified. To solve this problem, biometric authentication using EEG, which is difficult to obtain internal information and requires special measurement devices, has been studied. In the past studies on EEG authentication, it has been a challenge to find effective feature values in frequency bands of EEG signals. However, their authentication accuracies have been still lower than other methods of biometric authentication. In this study, we propose a method of EEG authentication by using multi-channel EEG recording, appropriate artifact removal, feature extraction, and machine learning towards improving the authentication accuracy.

II. METHODS

In the proposed method, a 32-channel recorder (EPOC Flex from Emotiv) is used to measure the EEG. The sampling frequency of the electroencephalograph is 128 Hz. The electrode configuration follows the international 10-20 method. 28 channels and 4 channels were used for EEG and EOG signals respectively. EEG signals were recorded on seven adult subjects in a sitting position in resting conditions with eyes-closed and eyes-open. In the eyes-open condition, the subjects looked at a gazing point displayed on a PC. Three trials of 60 s were measured in each condition for each subject. Artifacts were corrected by using the independent component analysis. The EEGs signals acquired in each trial were segmented into six epochs of 10 seconds each. A time-frequency analysis using the Morlet continuous wavelet transform was applied for the EEG data and 1280 (time) \times 54 (frequency) dimensional scalograms were extracted as EEG features[1]. A convolutional neural network (CNN) was trained to distinguish a person from other 5 individuals for each subject[2]. Input patterns of the CNN were the

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scalograms on the 28 channels and outputs of the CNN were the corresponding discrimination. For each training, we divided the data into training data (12 for the subject and 72 for others) and test data (6 for the subject and 36 for others). Three training data sets were made by replacing trials used for the test data. From the discrimination results of CNN on the test data, we calculated the acceptance rate (FAR) and the rejection rate (FRR). These values are the evaluation index of the system that shows the low misclassification.

III. RESULTS

Table 1 shows accuracy of the discrimination by CNN for test data (ACC), FAR, and FRR in eyes-closed and eyes-open conditions for all seven subjects. The values are the average of the three data sets.

Table 1 Average values of ACC, FAR, and FRR

subj. no.	eyes-closed condition			eyes-open condition		
	ACC	FAR	FRR	ACC	FAR	FRR
1	0.79	0.09	0.89	0.55	0.22	0.49
2	0.64	0.41	0.54	0.73	0.59	0.19
3	0.59	0.42	0.38	0.77	0.72	0.14
4	0.50	0.58	0.33	0.74	0.38	0.24
5	0.67	0.61	0.27	0.60	0.66	0.36
6	0.61	0.31	0.74	0.60	0.61	0.38
7	0.77	0.20	0.38	0.75	0.05	0.25

IV. DISCUSSION & CONCLUSION

The results of subject no.7 showed relatively high ACC, low FAR and low FRR in both conditions. The results show good performance as authentication. However, results of other subjects in the conditions showed that either FAR or FRR or both are high. Increasing number of subjects and verifying the difference in authentication accuracy due to changes in data length were required in the future works.

REFERENCES

- [1] H. Cecotti and A. Graser. (2010). Convolutional neural networks for P300 detection with application to brain-computer interfaces. *IEEE Trans. Pattern Anal. Mach. Intell.* 33, 433–445. doi:10.1109/TPAMI.2010.125
- [2] S. U. Amin et al., (2019). Deep Learning for EEG motor imagery classification based on multi-layer CNNs feature fusion. *Fut. Gener. Comput. Syst.* 101, 542–554. doi: 10.1016/j.future.2019.06.027